Detection of Eye Movements based on EEG Signals and the SAX algorithm

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Abstract. For patients with disabilities, particularly those with motor disabilities and difficulties to interact with computer and devices, Human-Machine Interaction (HMI) research may provide them new ways to solve this problem. In this paper, we propose the Brain-Computer Interface (BCI) approach as a potential technique. The patients may use a portable electroencephalography (EEG) device to give instruction to a computing device via eye movements. Classification algorithms have been investigated in past research to allow detection of eye movement. We would like to investigate another technique, namely the Symbolic Aggregate Approximation (SAX) algorithm, to find out its suitability and performance against known classification algorithms such as Support Vector Machine (SVM), k-Nearest Neighbour (KNN) and Decision Tree (DT).

Keywords: Brain-computer Interface · SAX · Eye movement.

1 Introduction

In many everyday activities today, interactions with technology are made easier with modern human-machine interaction (HMI) approaches. For example, one can use facial recognition to authenticate his identity or give instruction using gestures to interact with a large display dashboard. When it comes to assistive technology for users with disabilities, HMI will play an crucial role to provide accessibility to these users.

Users who belong to this category includes patients who suffer from amyotrophic lateral sclerosis (ALS), cerebral palsy or spinal cord injury. This group of users have very restricted movements and often will not be able to interact with a computer through conventional input approaches. One possibility is to use eye tracking as a computer input and interaction method [17][5]. However, eye gaze-based approach may face problem in determining a gaze from mere watch or gaze as an instruction [5]. Another option with potential is to utilize the brain-computer interface (BCI) to enable HMI. BCI is the approach that enables communication between a brain and a device. Suitable sensors are used to capture brain signals. These signals can be used with techniques, such as machine learning, to provide cues that may be interpreted as instructions.

Classification of eye movements using Electroencephalography (EEG) signal may become an attractive approach if the signals produced can generate distinguishable signal patterns between different movement classes. However, one needs to investigate the usage of portable EEG devices to enable usage of this type of HMI in more situations and environments. This also means there will be limited number of channels available, and signal sample may be considered as lower quality as compared to the laboratory grade EEG capturing devices. On top of this trade-off, one may also expect worst classification performance with fewer channels and reduced signal quality. We intend to apply suitable classification or pattern matching techniques on commercial-off-the-shelf (COTS) EEG devices and the algorithms should be producing good detection accuracy even though there may be limitation to the amount and quality of the data.

In this paper, we wish to investigate the suitability of the Symbolic Aggregate approximation (SAX) algorithm [12] in detecting simple eye movements from EEG signals. We argue that SAX may be a more efficient approach as compared to classification algorithms. The paper will present evaluation of the SAX algorithm used in detecting selected eye movement contexts.

The structure of the paper is as follow: Section 2 presents related work in the selected area of study. Section 3 introduces the proposed approach and the SAX algorithm. Section 4 discusses the obtained results and observations and the final section concludes the paper.

2 Related Work

Brain-computer interface (BCI) is a combination of hardware and software systems allow people with severe or partially disabled to communicate with their environment. BCI goal is to improve quality of life, and its full potential has yet explored. Much research has so far focused on people with severe motor disabilities. Example HMI is being investigated as techniques that use eye movements (EOG [3] or video-based eye gaze tracking [15]); body movement (limited limb movement, gestures head, facial expressions and so on.) [8] and brain signals (Electroencephalography - EEG) [7]. In this paper, the focus of the BCI technology will be based on EEG.

The first recorded electroencephalography effort is usually referred to the work of Hans Berger (1873-1941) in discovering and measuring electrical activity from the surface of the human head [4]. This marked the beginning of EEG technology. EEG has been used in laboratories settings for various purposes, including neuroscience, medical, cognitive science etc. The setup used in such settings are commonly complex and non-portable. It is only in the last decade, consumer grade EEG devices have been developed and made available in the market [10].

The usage of EEG as an BCI input device can be an attractive option for patients with movement disabilities, such as ALS or spinal cord injury. They can interact with computers and devices by using BCI approach. For example, Carrino et al. proposed to use an Emotiv EPOC device to enable control of an electric wheel-chair in a self-paced manner [6]. The investigation tested the EPOC using motor-imagery technique to perform wheel-chair control. The best results obtain was not higher than 60%. Another example is the work of Vourvopoulos and Liarokapis. They have investigated both Emotiv EPOC and Neurosky devices (Mindset and Mindwave) to evaluate their suitability in navigation [18]. The Emotiv EPOC gave better performance, though the authors mentioned that latency is an issue. Navuluri et al. carried out an investigation to predict drivers' intentions while driving using the Emotiv EEG device [16]. EEG signal has also been applied to control a 6-degree-of-freedom robotic arm [1], where an Emotiv EPOC was used for this purpose. The preliminary tests have verified that simple pick and place tasks can be performed by an operator after a relatively short learning period.

When it comes to algorithms for context detection using EEG signal, classification algorithms have been utilised in different previous work. Liu and Sourina applied Support Vector Machine (SVM) to enable detection of emotions using EEG signal obtained from an Emotiv EEG device [14]. In pattern recognition, the k-nearest neighbours algorithm (KNN) is a non-parametric methods used for classification. In the work of Li et al., they used KNN to detect three levels of attention [11]. There are also other techniques used such as Principle Component Analysis (PCA) [13], Independent Component Analysis (ICA) [2] and Multi-layer Perceptron [9].

3 Using SAX for Eye Movement Detection

In this paper, an investigation has been carried out to evaluate the feasibility of the SAX algorithm for eye movement context detection based on EEG signals. Apart from SAX, three classification algorithms have been selected for comparison purposes - Support Vector Machines (SVM), K-nearest Neighbour (KNN) and Decision Tree (DT). The SAX algorithm converts the EEG signals (each channel records signals that form time series) into symbolic sequences. It can be seen as an extension from the Piecewise Aggregate Approximation (PAA) technique. The latter divides a time series into equal parts. The arithmetic means of the signal points from each of these parts are then calculated. With the newly computed mean values, it forms new time series that may be better suited for pattern recognition. This is depicted in Figure 1, where the coloured level lines are the PAA representations.

The SAX algorithm extends PAA by converting the mean values into symbols, such as "*a*", "*b*" and "*c*" as shown in Figure 1. One can decide the number of symbols to be distributed, so that the relevant ranges will be defined to separate the PAA representation levels into repective "zones". As depicted as light grey lines around 0.5 and -0.5 in Figure 1, it divides the y-axis into three zones. Any mean levels belongs to the higher zone will be converted to the symbol "*c*". Similarly, the mean levels between -0.5 and 0.5 and below -0.5 will be converted

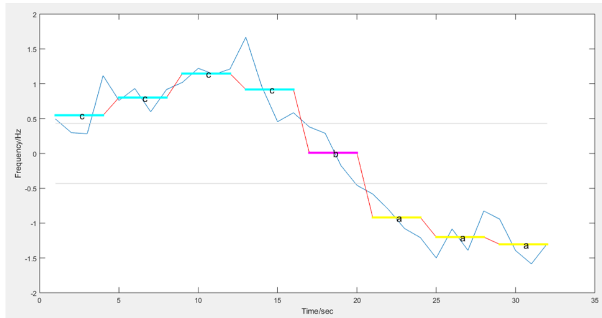

Fig. 1. Example representation of PAA and SAX from a time series

to "*b*" and "*a*" respectively. With this conversion, a symbolic string series is the new representation of the time series. For the time series in Figure 1, we then can say it is represented as "*ccccbaaa*" after applying the SAX algorithm.

The advantage the SAX algorithm brings is the possibility to apply string pattern matching techniques to detect patterns in time series. It also help to reduce the dimensionality of the original time series data. More importantly, there exist different string pattern techniques that are efficient and accurate. By enabling these existing techniques for time series pattern matching, it may help to improve the accuracy for the latter.

3.1 Data Collection and Experiment Setup

For the data collection, EEG data were recorded from 15 subjects (11 males, 4 females; age range 19 - 31). The subjects had normal or corrected-to-normal vision and had no history of neurological disorders. Each subject is requested to perform three types of movements - eye blink (*M1*), eyeball rotation (*M2*) as well as turning of eyeball to the left and right (*M3*). These movements have been selected as they are common movements used to instruct or interact with a computer. Each recording involved 10 repetitions of each movement respectively. These three movements data are the first three sets of measurement data. Besides these three sets of measurements, a forth set (*M4*) was collected from the subjects. This set contains all three movements.

The subjects were seated in a comfortable chair at a distance of approximately 70cm from a 13 inches (LCD) panel in the lab. The recording environment was kept from any external disturbance so that no one gets distracted during the recording. The screen is at eye level position. The subjects were instructed to relax and stay as placid as much as possible. This is to avoid any possible effect on EEG signals with muscle artefact. The overall preparation process takes less than 5 minutes. The experiments carried out during evening time where the participants able to concentrate without any lack of sleep. The timing for the movements in each recording was pre-defined. Hence, it is possible to label

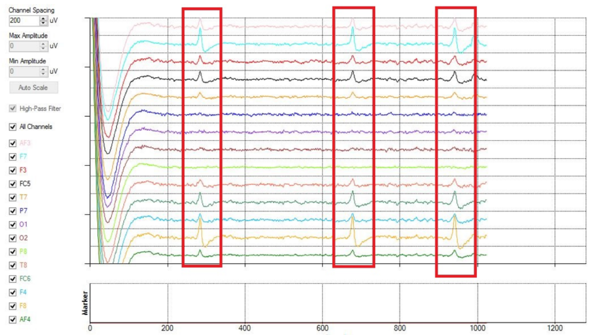

Fig. 2. Example EEG signal captured using Emotiv Testbench. Red boxes indicate eye blink movements.

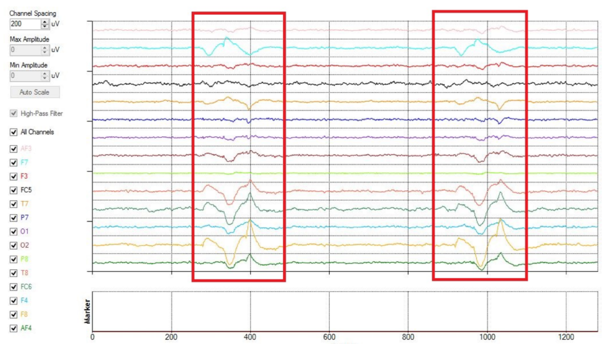

Fig. 3. Example EEG signal captured using Emotiv Testbench. Red boxes indicate eyeball rotation movements.

the recorded signal based on these timing. The labelled data will be used for classification training and evaluation.

As shown in Figure 2 and 3, there are regions of signals captured that displayed a spike or change in amplitude when an eye movement is carried out. If the signal patterns between non-movement and a movement are visually different or distinguishable, we would expect this pattern change behaviour can be made detectable using suitable machine learning techniques. Also, techniques such as SAX should also be able to distinguish signal patterns between non-movement and eye movements. The next sub-section will describe the steps carried out to process and analyse classification of EEG signal for eye movement detection.

3.2 Data Pre-processing and Classification

The raw EEG data was recorded using the tools provided by Emotiv EEG. The sampling rate of the raw data was 128Hz for all channels. First step of pre-processing was to perform basic filtering of the signal to reduce noise in

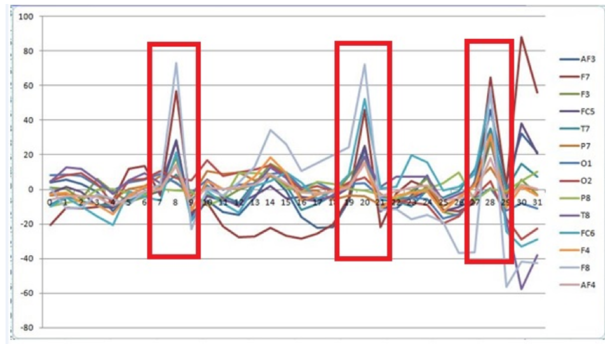

Fig. 4. Example mean feature extracted from EEG signal for the movement eye blink. Red boxes indicate eye blink movements.

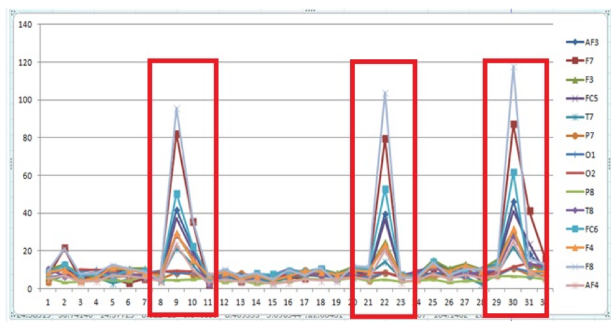

Fig. 5. Example standard deviation feature extracted from EEG signal for the movement eye blink. Red boxes indicate eye blink movements.

the EEG signals. EEGLAB toolbox was used to perform the feature extraction. For the classification of the movements, simple statistical features, namely mean and standard deviations, have been selected. The raw EEG signals was downsampled to 128Hz for all channels. For the feature extraction, the signals from each channel was segmented into windows of 0.25 seconds. No overlapping of window was used.

The features generated will be more useful for the intended classification and pattern recognition, because not only the process reduces the dimensionality of the original data, but it may also highlight particular signal characteristics of the signal, so that the patterns are more distinguishable among the different classes. For example, as shown in Figure 4 and 5, the computed features for selected channels are more distinguishable than the rest, and will be useful to produce models that can detect the expected movements.

The outcome of the feature extraction is used together with the labels at the corresponding timing of the windows as data for both training and testing. For the three classification algorithms, the classifier learner in MATLAB is se-

Table 1. Evaluation of Accuracy for all three classification techniques

	Average accuracy (%)		
Movement	SVM	KNN	DT
Eye blink	**86.87**	81.37	84.17
Eyeball rotation	**91.29**	87.39	88.70
Eyeball turn left & right	**83.65**	79.33	81.67
All three movements	**71.17**	68.35	69.33

lected to produce the desired models and perform the evaluation. As for SAX, the resulted time series of the features extracted will be converted into string sequences. For this paper, evaluation results for the string sequence length of four will be presented. Other lengths have been also used for comparison and a sequence of four string characters gave overall best outcome. From the training set, the string sequences that represent movements in each dataset were extracted. Evaluation for the classification is done by verifying the number of correctly matched movement string sequences with the test dataset.

4 Results and Discussions

Table 1 presents the summary of the classification accuracy for the SVM, KNN and DT algorithms. Generally, SVM performed the best among three algorithms for all four sets of data (*M1-M4*) (highlighted in bold). Second highest accuracy was produced by DT consistently across all four sets of movements data. Among the four set of data, the movement eyeball rotation achieved the highest accuracy (91.29%) with SVM. The forth dataset that contains all three movements in one measurement obtained the lowest accuracy as compared to the single movement measurements. The highest among the classification algorithms was SVM with 71.17%, following by DT (69.33%) and KNN (68.35%).

SVM performed better overall because its ability to detect best separation between classes and is not to sensitive to outliers. Nevertheless, the other two algorithms were not too much lower in the respective achieved accuracy for all four sets of measurements. The single movement measurements performed way better than the measurements that include all three movements (*M4*). This is mainly due to the more simplistic model for measurements (*M1-M3*). Each of these sets only contains patterns that different between a selected movement and no movement. The movements recorded in the forth data set (*M4*) are three different eye movements, but there could be similarity between them. This situation may caused the classification algorithms some trouble to successfully tell two or more movements apart.

The accuracy obtained from the evaluation of the SAX algorithm is found in Table 2. The evaluation was carried out under two different settings: SAX 1 used data from 10 subjects to extract top five the SAX movement string patterns then tested on the data from the exact same 10 subjects. SAX 2 used the same exact five patterns but tested them on measurement data from 5 subjects whose

Table 2. Evaluation of Accuracy for SAX

Movement	Average accuracy (%)		
	feature	SAX 1	SAX 2
Eye blink	mean	89.60	91.60
Eye blink	standard deviation	**92.60**	**93.60**
Eyeball rotation	mean	**88.40**	86.8
Eyeball rotation	standard deviation	83.20	**92.0**
Eyeball turn left & right	mean	**91.2**	**94.8**
Eyeball turn left & right	standard deviation	87.40	85.6

Table 3. Evaluation of Accuracy using SAX algorithm for all movements

Movement	Average accuracy (%)	
	Mean	Standard Deviation
All three movements	71.37	**90.29**

data was not part of the training data. The highest accuracy for each movement is highlighted in bold.

From Table 2, it is observed that generally eye movement detection using SAX algorithm performed better than the three classification algorithms. The only exception will be eye ball rotation movement, where the improvement may not be significant (SAX using standard deviation, 92% compared to SVM 91.29%). Also, the evaluation for SAX-based detection utilised only one single feature at a time. Comparing the settings SAX 1 to SAX 2 and which feature should be considered, we would want to discuss performance of SAX 2 as it was testing the model from SAX 1 on a new set of data from additional subjects. The evaluation results for SAX 2 may be closer to real world performance. For eye blink and eye rotation, the results from SAX applied on standard deviation feature only were higher than mean. For eye ball turn, the mean feature achieved the highest accuracy. From these results, the SAX technique does produce relatively better accuracy with only one feature used. It can be seen as more efficient in terms on computation.

As for the evaluation for all movements ($M4$) using SAX, the results are summarised in Table 3. The result using mean features and SAX performed similar to the result from SVM. But the accuracy achieved by SAX using only standard deviation is the highest among other two results. This also means that by using standard deviation to create string patterns using SAX, the movements patterns for all three movements can still be detected and distinguished from each other.

To investigate whether one can also use only one single EEG channel for eye movement detection, we analysed the detection accuracy based on single channel. The results is summarised in Table 4. It is observed that by selecting a particular channel only, one can achieved higher detection accuracy. Among all channels, the detection obtained by using only the channel T8 has almost 100% accuracy. While this may be too ideal, but the evaluation using individual

Table 4. Evaluation of Accuracy using SAX algorithm for all movements

Channel	Average accuracy (%)	
	Mean	Standard Deviation
F7	69.63	**78.14**
F8	50.37	**86.30**
FC5	94.81	**89.63**
FC6	73.70	**97.78**
T8	68.33	**99.63**

channel showed that one can use only one or two channels, such as T8 and FC6, for the movement detection to achieve good accuracy.

Overall, the movement detection using SAX algorithm showed positive results that indicated its potential to be a suitable technique for movement detection using EEG signal. As compared to typical classification algorithms such as SVM, KNN and DT, SAX algorithm allows accurate movement detection with only one feature extracted from one or two channels of EEG signal obtained from a COTS EEG device, such as the Emotiv EEG. This will allow better recognition efficiency since less data needs to be processed. It is also seen as attractive to be applied on resource limited situations such as wearable and portable EEG for everyday activity scenario.

5 Conclusion

In this paper, we have presented an investigation of EEG-based eye movement detection using three classification algorithms, namely SVM, KNN and DT, and SAX. It is observed that SAX-based approach achieved higher accuracy with fewer features and channels. This indicates a potential in using SAX for accurate eye movement detection in a resource-limited scenario, such as real-time eye movement detection using portable EEG device.

As future work, we wish to look into possibility to implement the identified best settings as a prototype wearable system that allows accurate eye movement detection using the Emotiv EEG device. This will allow us to verify and validate the results obtained in this investigation in a real-life scenario.

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